European Journal of Business and Management www.iiste.org
ISSN 2222-1905 (Paper) ISSN 2222-2839 (Online)
Vol.10, No.10, 2018

Forecasting OPEC Oil Price: A Comparison of Parametric Stochastic Models

Chioma N. Nwafor[1] Azeez A. Oyedele[2]
1.Glasgow School for Business and Society, Department of Law, Economics, Accountancy and Risk, Glasgow Caledonia University, Cowcaddens Road, Glasgow G4 0BA, United Kingdom
2.School of Business and Enterprise, University of the West of Scotland, Paisley Campus, Paisley PA1 2BE, United Kingdom

Abstract
Most academic papers on oil price forecasting have frequently focused on the use of WTI and European Brent oil price series with little focus on other equally important international oil price benchmarks such as the OPEC Reference Basket (ORB). The ORB is a weighted average of 11-member countries crude streams weighted according to production and exports to the main markets. This paper compares the forecasting accuracy of four stochastic processes and four univariate random walk models using daily data of OPEC Reference Basket series. The study finds that the random walk univariate model outperforms the other stochastic processes. An element of uncertainty was introduced into the point estimates by deriving probability distribution that describes the possible price paths on a given day and their likelihood of occurrence. This will help decision makers, traders and analysts to have a better understanding of the possible daily prices that could occur.
JEL Classification Numbers: E64; C22; Q30
Keywords: Oil Price Forecasting, Probability Distributions, and Forecast Evaluation Statistics, Brownian Motion with Mean Reversion process, GARCH Models

1. Introduction

The primary factors affecting fluctuations in oil prices are changes in supply and demand. However, the challenge for policy makers, analysts and traders is that there are several factors that can affect these fundamentals and many of them are interconnected. These factors include supply interruptions such as oil spills, emergence of alternative sources of energy, OPEC decisions, and escalation of conflicts in oil exporting nations amongst others, (Baffes et al, 2015 and U.S Energy Information Administration, 2017). In addition, meta-factors such as “fear” also play a large part, for example, the fear that a future event such as geopolitical risks that could affect supply and demand may happen. For instance, the 2014 violence in Libya resulted in major disruptions in oil exports leading to a rise in oil prices, Cunningham (2015). At about the same period, Islamic State in Syria (ISIS) took over some parts of Iraq, and oil prices shot up on fears of supply outages, Behar and Ritz (2014). While many analysts see-(Fattouh and Mahadeva, 2013; Huppmann and Holz, 2015; Huppmann and Holz, 2012) argue that coordination difficulties amongst OPEC member countries have significantly diminished their degree of market power, the fact that oil prices crashed after the cartel’s November 2014 meeting demonstrates how influential they are over price swings, Behar and Ritz (2014). While most studies that review the causes and implications of oil price crash attributes it to positive oil supply shocks in the second half of 2014, and weak demands, (Baffes et al, 2015; Beidas-Strom and Osorio-Buitron, 2015), Bhar and Ritz (2016) highlights the important role that OPEC’s interference in the international oil market has on oil prices. According to them, oil prices decline that is orchestrated by weakening global demand or an exogenous increase in supply can be exacerbated by OPEC member countries refusal to cut production. Arezki and Blanchard (2014) in their contribution attributed the 2014/15 oil price slump to a shift in market expectations about the future path of oil production following OPEC’s decision not to cut production to compensate for higher production from non-OPEC member countries.

Crude oil forecasting is difficult because of the interaction of these complex factors as well as the difficulty in determining the relative importance of each factor. Consequently, getting a forecast model that can act as a proxy for modelling changes in oil prices is of paramount importance for traders, analysts, researchers, businesses and governments that rely on oil as important sources of revenue. Fattouh et al (2015) argues that Saudi Arabia and many other OPEC countries remain undiversified in their sources of foreign revenue and therefore, relies on revenue from oil for meeting domestic spending. Indeed for these countries, revenue from oil is a prime consideration in their budgetary processes. This paper compares the forecasting ability of eight time series models using daily data of spot OPEC Reference Basket[1] (ORB) oil prices. from January 3rd 2003 to March 10th 2017, (3663 observations) The dataset was divided into two parts; 01/02/2003 to 12/30/2016 this is the in-sample period, used for the initial parameter estimation and model selection. The second part; 01/03/2017 to 03/10/2017 is the out-of-sample period, used to evaluate forecasting performance. The forecast accuracy of the following models:

[1] ‘OPEC Basket’ is a weighted average of oil prices collected from various oil producing countries. The average is based on the production and exports of each OPEC member country and is used as a reference point by OPEC to monitor the conditions of oil markets world-wide.

Autoregressive models AR (1) and AR (2), Moving Average models, MA (1), MA (2), Autoregressive moving average ARMA (1, 1), Autoregressive Conditional Heteroscedasticity ARCH (1), Generalized Autoregressive Conditional Heteroscedasticity GARCH (1, 1,), Brownian Motion with Mean Reversion process (BMMR), and Brownian Motion with Mean Reversion and Jump Diffusion process (BMMRJD) were evaluated using eight forecast evaluation statistics.

The OPEC Reference Basket (ORB) is a weighted average of 11 member country crude streams including: Saharan Blend (Algeria), Girassol (Angola), Oriente (Ecuador), Iran Heavy (Islamic Republic of Iran), Basra Light (Iraq), Kuwait Export (Kuwait), Es Sider (Libya), Bonny Light (Nigeria), Qatar Marine (Qatar), Arab Light (Saudi Arabia), Murban (UAE) and Merey (Venezuela), OPEC (2016) World Oil Outlook (WOO). These represent the main export crudes of all member countries, weighted according to production and exports to the main markets. The ORB is used as a reference point by the organization to monitor worldwide oil market conditions, WOO (2016). While previous studies on oil price forecasting have frequently focused on the use of WTI and European Brent oil price series, this study is the first study to the best of our knowledge to apply these stochastic models to the ORB oil price benchmark. This is important because OPEC is a cartel that tries to manage the supply of oil in a bid to influence the price of oil on the world market, so as to avoid fluctuations that might affect the economies of both producing and purchasing countries. This makes the ORB measure important for market analysts.

This study is significant in two ways. First, while most oil price forecasting studies have focused on different measures of forecast error when determining the best forecasting model, this study compares the actual prices with the forecasted prices over a one month period and evaluates the forecasts on the basis of their ability to minimize forecast errors using eight different criteria. The result shows that the GARCH model can provide more accurate price forecasts than the other stochastic models used in the study-(more on this in the subsequent sections). Second, we incorporate an element of uncertainty into the daily point forecasts using probability distribution. This allows the forecaster to graphically see the range of possible daily prices and their probability of occurrence. The findings from these analyses will be relevant to private businesses that use oil as a major production input, and OPEC member countries that need accurate forecasts of the price of oil for medium term revenue planning as well as crude oil traders and analysts. The rest of the sections are structured as follows; section 2 presents a brief review of previous literatures on stochastic models. In section 3 we present data analysis, and unit-root test, section 4 is the model specifications and parameters. Section 5 is the forecast evaluation statistics and interpretation of the forecast results while section 6 is the summary and conclusion.

2. Literature review

Crude oil is one of the main inputs in forecasting macroeconomic variables such as inflation, GDP, exchange rate, amongst others, Kilian and Vigfusson (2013). As a result, the forecasting of crude oil has being a subject of interest to academic researchers. The use of univariate models and the evaluation of their forecasting abilities were motivated by the study of Messe and Rogoff (1983) where they provide evidence that random walk models outperformed the complex structural models in forecasting exchange rate variables. Since then, plethora of studies have been carried out, some corroborating the findings of Messe and Rogoff, others supporting the use of economic fundamentals in determining exchange rate behaviour.

There are two main strands of literatures on modelling oil price behaviour; the first strands are studies that are conducted in the context of stochastic processes by means of simulated data based on Monte Carlo experiments, Clements and Smith (1997, 1999). Some of these studies suggest geometric Brownian motion and other mean reversion models, Brennan and Schwartz (1985). These studies mostly focus on the dynamic representation of oil prices and on their short-run predictability. The main premise of these univariate stochastic models is the efficient market hypothesis which suggests that if the oil market is characterized by some level of efficiency, it is reasonable to assume that all the relevant publicly available information are already incorporated in the most recent prices. Consequently, it becomes unnecessary to include the economic fundamentals in the set of independent variables, Nigel (2010).

The second strands are empirically driven literatures with endogenous regressors' selected according to economic theory (i.e. determinants of oil prices). These empirical literatures suggest the use of structural models such as ARMA, GARCH and VAR models amongst others, Cabedo and Moya (2003), Panas and Nini (2000), and Hung et al (2007), Baumeister and Kilian (2014b) and Alquist, Kilian and Vigfussion (2013), Kilian and Murphy (2014). The study of Tang and Hammoudeh (2002) is worthy of mention because the authors used the monthly spot OPEC basket crude oil price to investigate OPEC's attempts to control prices within a target zone model[1] during 1988 and 1999. Their study finds evidence that OPEC supported target zone model during the period. Tang and Hammoudeh (2002) specified an oil price structural model based on production quotas, inventory levels and an expectation term. Their study reveals that the out-of-sample forecast results of the target zone model performs

[1] They used the target zone model proposed by Krugman (1991) and concluded that OPEC has strong incentive to support a lower limit for oil price because high oil prices will encourage investment by non-OPEC nations and reduce the market share of OPEC member countries. Consequently, OPEC has a strong reason to put an upper limit for oil price.

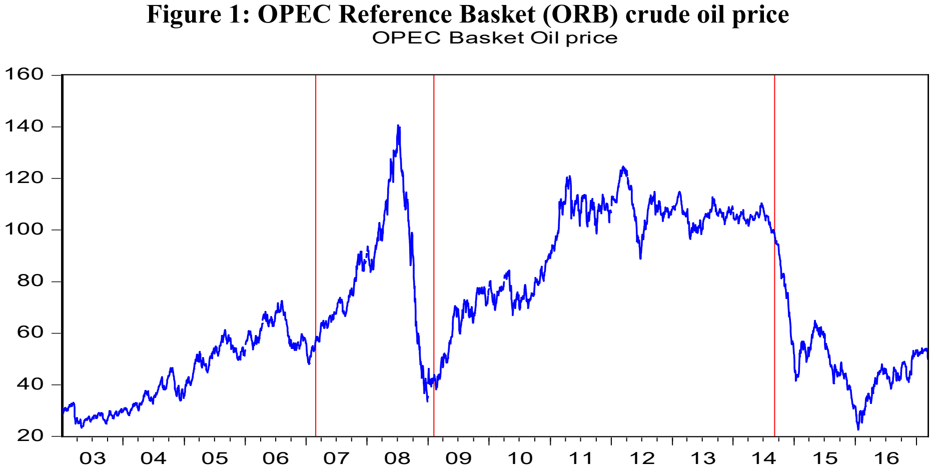
better than other structural forecasting models based on supply and demand. Sadorsky (2006) in his study reveals that the out-of-sample forecasts of univariate GARCH model performs better than the VAR models in forecasting petroleum futures volatility. Other studies posit the use of a density function for the future price of oil, Nigel (2010).

The current paper takes the view that forecasting crude oil prices by considering its' determinants may not be plausible because there are so many factors that cause changes in prices and all these factors may not fit into a structural model. Indeed, Gooijer and Hyndman (2006) suggest that most VAR models produce poor out-of-sample forecasts because they tend to suffer from 'overfitting' that is inclusion of redundant variables. The present study departs from previous studies by comparing the forecasting performance and accuracy of the different univariate models of oil price behaviour proposed in the literature and then use probability density function to account for the uncertainty associated with the point forecasts.

3. Data analysis, and unit-root test with breakpoint

This study uses daily data of OPEC Reference Basket (ORB) spot oil price series from January 3rd 2003 to March 10th 2017 to compare the out-of-sample forecast accuracy of eight time series models. The price series was sourced from the Organization of Petroleum Exporting Countries database. The graph shows periods of both sustained increases and declines in oil price. A simple visual inspection of the graph reveals the presence of trend and an obvious jump down for most of the series occurring in 2009, and second half of 2014. Specifically, the oil price appears to follow long swings- up-ward trend for a period of time, and then switches to a period of downward trend.

Figure 1: OPEC Reference Basket (ORB) crude oil price



Data source: Organization of the Petroleum Exporting Countries database

Table 1: Descriptive statistics of the OPEC Reference Basket oil price

Mean	\$70.24
Median	\$65.48
Maximum	\$140.73
Minimum	\$22.48
Standard Deviation	\$29.11
Observations	3663

The descriptive statistics reported in table 1 above suggests that the average price of ORB during the sample period is \$70.24. The maximum and minimum price during the period stood at \$140.73 and \$22.48 respectively, suggesting a large price drop. Next we test for the existence of a unit root in levels taking into account structural breakpoint(s) in the data. According to Perron (1989, 2006) the conventional unit root tests are biased toward a false unit root if there is an existence of structural break in a trend stationary series. Hansen (2001) provides an overview of empirical literatures that outlined various unit root tests that remain valid even in the presence of structural breaks. In line with Vogelsang and Perron (1998), we focused on endogenous determination of break dates from the data using Perron (1989) 'Innovational Outlier (IO) Tests' for modelling the break dynamics. This test evaluates the null hypothesis that the data follow a unit root process,

$$y_t = y_{t-1} + \beta + \psi(L)(\theta D_t)(T_b) + \gamma(DU_t)(T_b) + \epsilon_t) \qquad (1)$$

Where ϵ_t are $i.i.d$ innovations, and $\psi(L)$ is a lag polynomial representing the dynamics of the stationary and invertible ARMA error process, Eviews (2017). The break variables β, θ, γ and ω enter the model with the same dynamics as the ϵ_t innovations. For the alternative hypothesis, a trend stationary model with breaks in the intercept and trend is assumed:

$$y_t = \mu + \beta t + \psi(L)(\theta DU_t(T_b) + \gamma DT_t(T_b) + \epsilon_t) \qquad (2)$$

Just as in equation 1, the breaks in equation 2 follow the innovation dynamics. A general Dickey-Fuller test equation which nests the two hypotheses can be written as;

$$y_t = \mu + \beta t + \theta DU_t(T_b) + \gamma DT_t(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \mu_t \qquad (3)$$

The t-statistic is used to compare $\hat{\alpha}$ to $1(t_{\hat{\alpha}})$ to evaluate the null hypothesis. The k lagged differences of y are included in the test equations to eliminate the effect of the error correlation structure on the asymptotic distribution of the statistic. Perron (1989), and Vogelsang and Perron (1998), highlights four different specifications for the Dickey-Fuller regression each corresponding to different assumptions for the trend and break behaviour. This study considers a trending data with intercept and trend break;

$$y_t = \mu + \beta t + \theta DU_t(T_b) + \gamma DT_t(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + u_t \qquad (4)$$

Equation 4 tests the random walk with drift against a trend stationary with intercept and trend break alternative. The result of the unit root test in table 2 suggests the presence of unit root and break in the data. The test results in a t-statistic of -4.40, with a $p-value$ greater than 0.01, leading us not to reject the null hypothesis of a unit root.

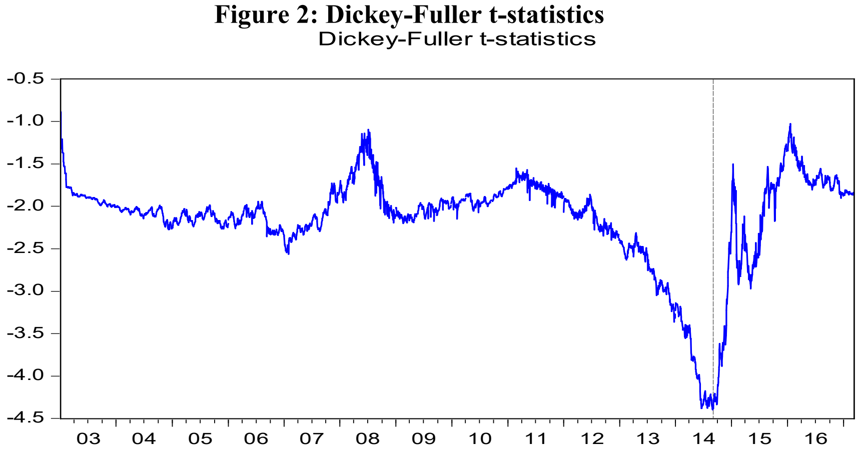
Table 2: Unit root with break test on OPEC Reference Basket (ORB)

	t-Statistic	Prob*
Augmented Dickey-Fuller test statistic	-4.40	0.17
Test critical values: 1% level	-5.35	
5% level	-4.86	
10% level	4.61	

Note: Null hypothesis is OPEC has a unit root, trend specification: trend and intercept, break specification: Innivational outlier and break date is 9/01/2014, which is the break date for the start of the new regime as opposed to the last date of the old regime. Lag length selection based on $t-statistic\ selection$ (lags 0 to 29) *Vogelsang (1993) asymptotic one-sided $p-values$.

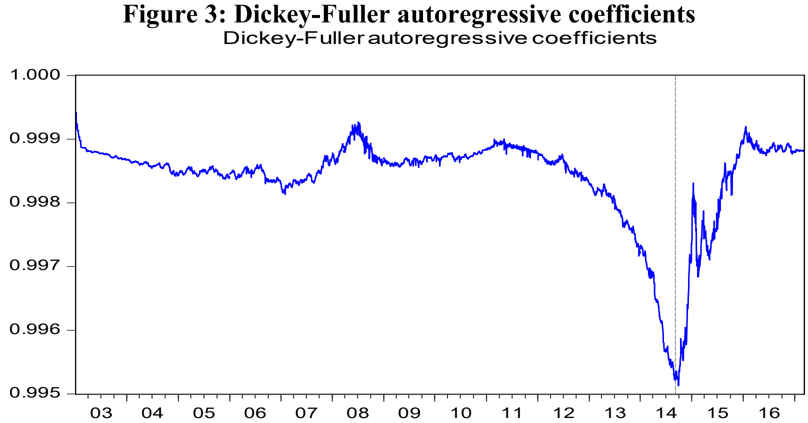
The graphs of the Augmented Dickey-Fuller statistics and AR coefficients at each test date are reported below. Both graphs reveal a large drop in 09/01/2014, confirming the presence of break in the data and leaving no doubt as to which date should be selected as the break point.

Figure 2: Dickey-Fuller t-statistics



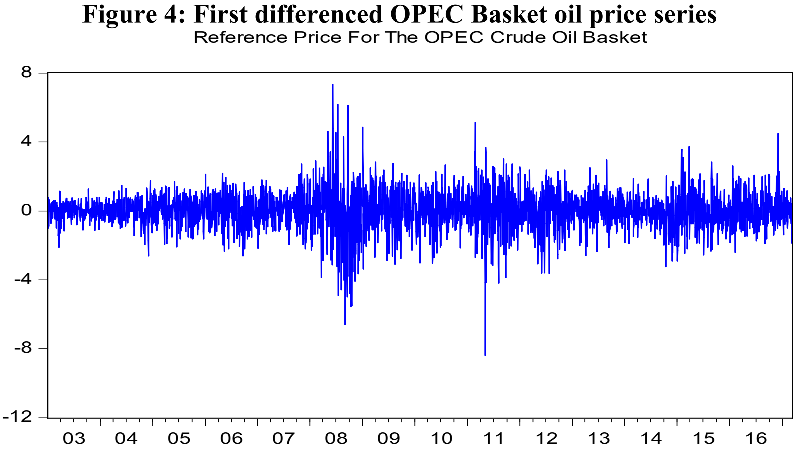
Data source: Organization of the Petroleum Exporting Countries database

Figure 3: Dickey-Fuller autoregressive coefficients



Given that stationarity is one of the major criteria in time series modelling and forecasting, that is the mean and standard deviation are expected to be constant through time; the data was de-trended and it became stationary after first differencing- see figure 4.

Figure 4: First differenced OPEC Basket oil price series



4. Model specifications and interpretation of results

We turn our attention to the analysis of Autoregressive Moving Average (ARMA) processes, Autoregressive Conditional Heteroskedasticity (ARCH) and its variations, as well as Brownian motion and its variations. The central idea here is to identify the processes that are most in line with the historical oil price data. The ARMA processes were developed by Box and Jenkins (1976); these models are particularly useful when economic theory is not an important consideration. According to Box et al (1994), the ARMA methodology does not assume any particular pattern in a time series; however, it uses an iterative approach to identify a possible model from a general class of models. Given that all of these methods are well documented in the literature[1], we simply outline them below. An autoregressive model of order p, denoted $AR\ (p)$ has the form;

$$Y_t = \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + \cdots + \rho_p Y_{t-p} + \varepsilon_t = \sum_{j=1}^{P} \rho_j Y_{t-j} + \varepsilon_t \qquad (5)$$

Where ε_t are the independent and identically distributed innovations for the process and the autoregressive parameters ρ_i describe the nature of the dependence. We implemented $AR1\ (\mu, \sigma, \beta_1, Y_0)$ where, μ is the mean, σ is the volatility parameter, β_1 is the autoregressive coefficient, and Y_0 is the value at time 0, and AR 2 that generates a second-order autoregressive process with mean μ, volatility parameter σ, autoregressive coefficients $\beta_1, and\ \beta_2$, and values Y_0 and Y_{-1} at times 0 and -1. ARMA (1,1) $(\mu, \sigma, ar_1, ma_{1,} Y_{0,} \varepsilon_0)$ generates a first-order autoregressive moving average (ARMA 1,1) process with mean μ, volatility parameter σ, autoregressive coefficient ar_1, moving average coefficient ma_1, and value Y_0 at time 0, and initial error term ε_0.

ARCH I $(\mu, \omega, \beta_{1,} Y_0)$ generates a first-order autoregressive conditional heteroskedasticity process with mean μ, volatility parameter ω, error coefficient β_1, and value Y_0 at time 0. GARCH (1,1) $(\mu, \omega, \beta_1, ar_1, Y_0, \sigma_0)$ generates a Generalized ARCH process with mean μ, volatility parameter ω, error coefficient β_1, autoregressive coefficient ar_1, value Y_0, at time 0, and initial standard deviation σ_0. GARCH is a generalization of the original ARCH model, where the model for the conditional variance at time t is a weighted combination of three terms; the volatility parameter ω, the previous squared deviation from the mean, and the previous variance. The GARCH model states that the conditional variance of asset returns in any given period depends upon a constant, the previous

[1] For a full discussion on the procedure refer to Box et al (1994), Pindyck and Rubinfeld (1998) and Gourieroux and Monfort (1995).

period's squared random component of the return and the previous period's variance; Engle and Bollerslev (1986). Moving average (MA) methods are mostly used in forecasting because they often provide a good fit and they are simple to apply. The moving average technique uses an average of past observations to smooth short-term fluctuations, Dunis, Laws and Naim (2003).

We used MA 1 process which is characterized by an autocorrelation function (ACF) that cuts off to 0 after lag 1 and a partial autocorrelation function (PACF) that decreases geometrically. The $MA\ 1\ (\mu, \sigma, \beta_1, \varepsilon_0)$ generates a first-order moving average process with mean μ, volatility parameter σ, moving average coefficient β_1 and the initial error term ε_0. The $MA\ 2\ (\mu, \sigma, \beta_1, \beta_2, \varepsilon_0, \varepsilon_{-1})$ generates a second-order moving average process with mean μ, volatility parameter σ, moving average coefficients β_1 and β_2, and initial error terms ε_0 and ε_{-1}. An MA 2 process is characterized by an autocorrelation function (ACF) that cuts off to 0 after lag 2, and a partial autocorrelation function (PACF) that decreases geometrically.

The Brownian motion with Mean Reversion process (BMMR) was originally proposed by Vasicek (1977) as a model for interest rates. This model is predicated on the premise that some economic variables cannot rise indefinitely because of economic forces; they tend to revert back to some long-term average value. According to Vasicek (1977), a mean reverting model will tend toward a long-run equilibrium mean; therefore, when the series is above this level, it will tend to decrease, and vice versa. The following parameters $(\mu, \sigma, \alpha, Y_0)$ generates a Brownian motion with mean reversion process with long-term mean parameter μ, volatility parameter σ, speed of reversion parameter α, and value Y_0 at time 0. Finally, the Brownian motion process with mean revision and jump diffusion (BMMRJD) combines the BMMR and jump diffusion. The following parameters $\left(\mu, \sigma, \alpha, \lambda, \mu_J, \sigma_J, Y_0\right)$ generate a Brownian motion process with mean reversion and jump diffusion. μ_J is the jump size mean, and σ_J is the jump size standard deviation. The model parameters are reported in table 5 below.

Table 5 Parameter estimates for the univariate stochastic models

	GARCH 1,1	MA 1	MA 2	AR2	ARMA 1.1	BMMR	AR 1	ARCH1	BMMRJD
μ	0.006481	0.006481	0.006481	0.006481	-0.047031	0.0061967	0.0064812	0.006481	-0.0511
σ		1.0306	1.0342	1.0334	1.0334	1.763	1.0356		1.6534
β_1	0.053097	0.27165	0.27165	0.27516			0.25856	0.009730	
β_2			-0.006621	-0.064223					
ar_1	0.91324				0.047237				
ma_1					0.23128				
Y_0	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Y_{-1}				1.14					
ε_0		-0.21072	-0.21303		-0.18048				
ε_{-1}			1.0104						
ω	0.02562							1.0865	
σ_0	0								
λ									0.0187
α						1.3529			1.4064
μ_J									3.088
σ_J									2.730

Where, μ is the mean, σ is the volatility parameter, $\beta_1, and\ \beta_2$ autoregressive coefficients, and values Y_0 and Y_{-1} at times 0 and -1, ar_1 is autoregressive coefficient, ma_1 is the moving average coefficient, $\varepsilon_0\ and\ \varepsilon_{-1}$ are the initial error terms, α is speed of reversion parameter. ω is the volatility parameter for the ARCH model and β_1 is the error coefficient from the ARCH model the parameters for the BMMR and BMMRJD are $\mu, \sigma, \alpha, \lambda, Y_0\ and$ $\mu, \sigma, \alpha, \lambda, \mu_j, \sigma_j, Y_0$ respectively. Where μ is the drift parameter, σ, is the volatility,α is the speed of reversion, λ is the jump rate, μ_j is the jump size mean, σ_j, is the jump size standard deviation and Y_0, is the value at time 0.

5. OPEC Reference Basket oil price forecast evaluation statistics

This section compares the forecasting ability of the following time series models; Autoregressive models AR(2), Moving Average models, MA(1), MA(2), Autoregressive moving average ARMA (1,1), Autoregressive Conditional Heteroscedasticity ARCH (1), Generalized Autoregressive Conditional Heteroscedasticity GARCH (1,1,), with the following stochastic processes; Brownian Motion with Mean Reversion process (BMMR), and Brownian Motion with Mean Reversion and Jump Diffusion process (BMMRJD). The forecast error in each period is computed as;

$$e_t = y_t - f_t \quad (6)$$

Where e_t is the forecast error at time t, y_t is the observed price at time t, and f_t is the forecasted price at time t. Our objective is to select models that minimize e_t using eight forecast accuracy evaluation statistics. We compare and evaluate the in-sample forecasts of all the eight approaches using the Mean Error (ME), the Mean

Squared Error (MSE), the Mean Absolute Error (MAE), the Mean Percentage Error (MPE), the Mean Absolute Percentage Error (MAPE), the Root Mean Squared Error (RMSE) and Theil's U-statistics ($U_1 and\ U_2$) see (Theil 1966; Pindyck and Rubinfeld, 1998; and Nwafor and Oyedele, 2017) for a detailed description of the forecast evaluation statistics[1]. Hyndman and Koehler (2006) suggest the use of scaled errors as the standard measure for forecast accuracy. We have not used them in this study because the series in question is of the same scale.

We divided the datasets into two parts, 01/02/2003 to 12/30/2016[2]; this is referred to as the 'warm-up sample'. This sample is used to establish the parameters for the forecasting model and the second part, 01/03/2017 to 03/10/2017 referred to as the forecasting sample is used to measure the accuracy of the models. In other words, the accuracy of the model is measured over data that was not used to develop the model. This provides a good indication of the model's ability to forecast into the unknown performance. For each of these statistics, a smaller value indicates better forecast.

Table 6: Forecast evaluation statistics results

	GARCH 1,1	MA 1	MA 2	AR2	ARMA 1.1	BMMR	AR 1	ARCH1	BMMRJD
ME	0.24	0.62	0.69	0.69	0.48	1.55	2.81	0.06	0.46
MAE	0.90	1.66	1.59	1.59	1.60	2.20	3.86	1.91	1.99
MSE	1.55	3.82	3.69	3.69	3.40	7.04	23.46	5.13	5.65
MPE	0.42	1.18	1.26	1.26	0.91	2.89	5.25	0.06	0.88
$MAPE$	1.71	3.16	3.03	3.03	3.02	4.17	7.30	3.63	3.79
$RMSE$	0.90	1.66	1.59	1.59	1.60	2.20	3.86	1.91	1.99
$Theil's\ U_1$	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.01
$Theil's\ U_2$	1.97	3.03	3.00	3.00	2.86	4.16	7.60	3.57	3.74

ME denotes the mean error, MAE denotes the mean absolute error, MSE denotes the mean square error, MPE denotes the mean percentage error, MAPE is the mean absolute percentage error, RMSE is the root mean square error, Theil's U-statistics is presented in both of its specifications, these were labelled U_1 and U_2 ; the more accurate the forecasts, the lower the value of Theil's U, which has a minimum of 0. The MAE, MSE and $RMSE$ statistics are scale-dependent measures that allow a comparison between the actual and forecast values, the lower the values the better the forecasting accuracy. The $MAPE$ and $Theil - U$ are used to evaluate the forecast errors independent of the scale of the variables.

The results (table 6) above suggests that the GARCH (1,1,) model performs better than all the other stochastic models. This model has the least mean error (0.24), the least mean absolute error (0.90) the least mean square error (1.55), the lowest mean absolute percentage error (1.71), the lowest root mean square error (0.90) and the lowest $Theil's\ U_1 \& U_2$ statistics at 0.00 and 1.97 respectively. Using the mean percentage error as the evaluation criterion reveals that the ARCH (1) model performs slightly better than the GARCH (1, 1,) model at 0.06 for ARCH 1 and 0.42 for GARCH (1,1,). The result reveals that this model provides a good approximation of the likely daily price paths of the OPEC reference basket.

For many traders, decision makers and analyst's price forecasts are more important than statistical performance measures reported in table 6 above, since money can be made or lost by being able to determine if the price tomorrow Y_{t+1} is likely to increase or decline. In other words, statistical performance measures are not enough when it comes to practical applications. Kaastra and Boyd (1996: p229) put it succinctly when they noted that "*low forecast errors and trading profits are not synonymous since a single large trade forecasted incorrectly…could have accounted for most of the trading system's profits*". Consequently, we reported a comparison of the actual prices with the point estimates from GARCH (1, 1) in table 7.

[1] Note that different measures of accuracy may rank forecasts differently. A forecast is generally considered good if it correctly predicts price or direction of price movement

[2] This sample period was selected to ensure that we have enough observations in the warm-up sample to cover any seasonality.

Table 7: Point estimates and price differentials between the actual and simulated price

Trading day	Date	Actual price $	GARCH (1,1) Simulated price	Price differential
1	2017-01-03	53	53	0
2	2017-01-04	53	53	0
3	2017-01-05	53	53	0
4	2017-01-06	54	53	1
5	2017-01-09	53	53	0
6	2017-01-10	51	52	-1
7	2017-01-11	51	51	0
8	2017-01-12	52	51	1
9	2017-01-13*	53	51	2
10	2017-01-16	52	51	1
11	2017-01-17	53	51	2
12	2017-01-18	52	51	1
13	2017-01-19	51	51	0
14	2017-01-20	52	51	1
15	2017-01-23	52	52	0
16	2017-01-24	53	52	1
17	2017-01-25	52	52	0
18	2017-01-26	53	53	0
19	2017-01-27	53	53	0
20	2017-01-30	53	52	1

* A probability distribution that shows the probabilities of the possible prices for this date is shown in figure 5

Table 7 reveals a very close price margin between the actual and the forecasted prices. In 10 out of the 20 trading days we see that the forecasted prices are exactly the same as the actual prices. Essentially, this model produces superior point forecasts when compared with a range of alternative forecasting models considered. Given that risk matters and it affects how decision makers and investors make decisions, measuring risk is therefore, a first step towards managing it. Consequently, we introduce an element of uncertainty into the point estimates by using Monte Carlo simulation. With this technique, a probability distribution that describes the range of possible prices for a specific date is substituted for its point forecasts. Given the limitations of space, the current study reported simulation for one day. We simulate the likely daily price paths of the OPEC basket reference price on 2017-01-13[1] and their probabilities of occurrence. The goal is to derive probability distribution-see figure 5 below, that describes the possible prices on that day. The provision of probability distribution for the future likely price paths, including possible skewness[2] and kurtosis[3], will lead to a more enlightened decision as opposed to relying on point forecasts alone.

[1] Please, note that the choice of this date does not hold any practical significance. You can choose any date and perform the same simulations.
[2] Skewness measures the degree of asymmetry of a price distribution around its average price. The probability distribution in figure 5 reveals a positive skewness which indicates a distribution with an asymmetric tail extending toward more positive prices. In using this moment as a measure of risk, investors normally focus on downside risk. A symmetric (normal) distribution has a skew of zero.
[3] Kurtosis refers to the degree of peak in the price distribution. A normal distribution has a kurtosis of 3, excess kurtosis are kurtosis above or below 3.

Figure 5 Likely price paths on 12th January 2017

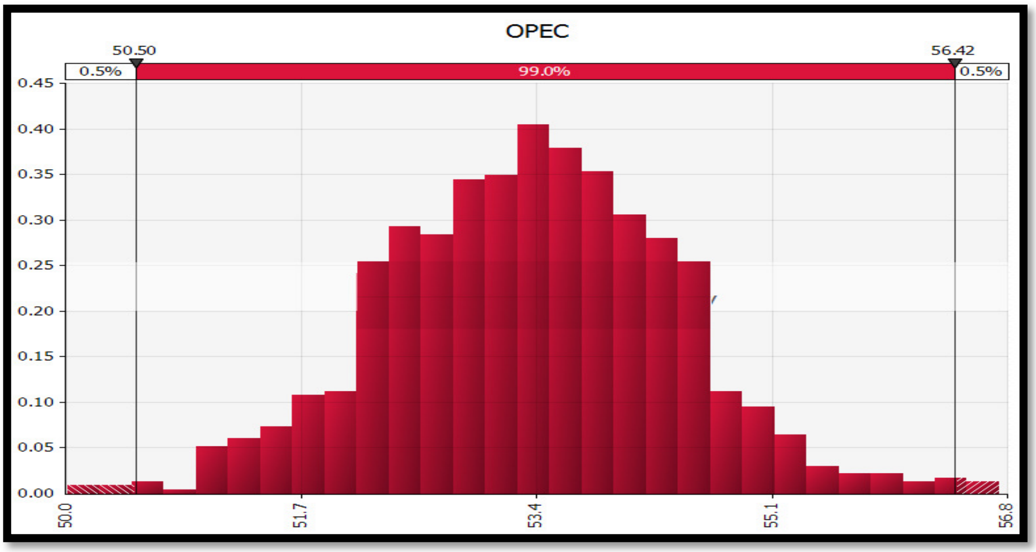


Figure 5 shows that at a 99.0% confidence interval the maximum price for this particular trading day will be \$56.42 and the minimum price is \$50.50. There is only a 0.05% chance that the price will fall below \$50.50 and 0.05% that it will increase above \$56.42. The statistics from the Monte Carlo simulation is presented in the table 8 below.

Table 8: Monte Carlo simulated price paths statistics in dollars (\$)

Minimum price	\$50.00
Maximum price	\$56.74
Average price	\$53.36
Median price	\$53.39
Standard deviation	1.04
Skewness	0.02
Kurtosis	3.30

According to table 8, we expect the price of this oil benchmark as at this date (2017-01-12) to trade around \$53.36. Specifically, the result from the Monte Carlo simulation indicates that the daily price could be anywhere between \$50 and \$56.74. The standard deviation which is a measure of the dispersion of the possible price paths from the expected price is \$1.04. Similarly, the shape of the daily price distribution reveals a slightly positive skew; indicating regular small losses and a few extreme gains. In addition, the distribution shows an excess positive kurtosis of 0.3 (3.30-3). This means that the distribution is leptokurtic indicating thicker tail than a normal distribution. The large volatility in oil price quantified to be more than 37% a year, and 2.5 times that of US stock market, Aloui and Mabrouk (2010), underscores the importance of using simulation to consider all possible daily price paths and their probability of occurrence. By looking at the spread and likelihoods of possible prices, traders and analysts can make an informed decision based on the level of risk they are willing to take.

6. Summary and conclusion

The results of this study indicate that the GARCH (1, 1) model outperforms the Autoregressive models AR (1) and AR (2), Moving Average models, MA (1), MA (2), Autoregressive moving average ARMA (1,1), Autoregressive Conditional Heteroscedasticity ARCH (1), Brownian Motion with Mean Reversion process (BMMR), and Brownian Motion with Mean Reversion and Jump Diffusion process (BMMRJD) models in forecasting OPEC reference basket oil price. The forecasts generated from the GARCH model generally have lower forecast errors and produced forecast values that are very close to the actual prices. Specifically, the forecasted prices were compared with the actual prices between 2017/01/03 and 2017/01/30; the results reveal that in 10 out of the 20 trading days, the forecasted prices were approximately the same as the actual prices. During the remaining 10 days, the forecasted prices missed the actual prices by a maximum of $\pm$\$2. We used Monte Carlo simulation to generate a probability distribution that describes the range of possible prices with their probability of occurrence for a specific date.

This technique overcomes the limitations of point estimates and assists decision makers in making more robust 'risk-based' decisions. Specifically, traders and analysts can see the range of possible prices on the 12th of January 2017 or any other date. Figure 5 above allows one to see the probabilities and understand the risks involved more clearly. The current study contributes to crude oil forecasting literature by not just reporting the forecast evaluation statistics (table 6) but also comparing the simulated prices with the actual prices see-(table 7). From a government perspective, reliable forecast of the price of oil for countries like Nigeria, Angola, and Saudi Arabia etc. is of extreme importance because oil price is a key variable in these countries national budgets. An important extension/improvement to this paper would be to assess the accuracy of the forecasting models using high-frequency intra-day data. Finally, it would also be interesting to assess the out-of-sample forecast accuracy of different variants of regime-switching models.

References

Aloui., C., and Mabrouk., S., (2010), "Value-at-Risk Estimations of Energy Commodities Via Long-Memory Asymmetry and Fat-tailed GARCH Models", Energy Policy, Vol. 38, Issue 5, Pp. 2326 – 2339

Alquist, R., Kilian, L., and Vigfusson, R. J., (2013), "Forecasting the Real Oil Price", in: Elliott, G., and Timmermann, A., (eds.), Handbook of Economic Forecasting, 2, Amsterdam: North-Holland, 427- 507.

Arezki, R., and Blanchard, O. J., (2014), "The 2014 Oil Price Slump: Seven Questions about the Recent Oil Price Slump", iMFdirect blog, available at https://blogs.imf.org/2014/12/22/seven-questions-about-the-recent-oil-price-slump/ accessed on 7/06/2017.

Baffes, J. M., Ayhan, K., Franziska, O., and Marc, S., (2015), "The Great Plunge in Oil Prices: Causes, Consequences, and Policy Responses", Development Economics Group Research Note, PRN/15/01. World Bank.

Baumeister, C., and Kilian, L., (2015), "Understanding the Decline in the Price of Oil Since June 2014", CEPR Discussion Paper, 10404

Baumeister, C. and Kilian, L., (2014b), "What Central Bankers Need to Know About Forecasting Oil Prices," International Economic Review, 55, 869-889.

Bauwens, L., Preminger, A., and Rombouts, J. V. K., (2010), "Theory and Inference for a Markov Switching GARCH Model", The Econometrics Journal, Vol. 13, Pp. 218 – 244

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C., (1994), Time Series Analysis: Forecasting and Control, Prentice Hall, Englewood Cliffs, NJ.

Brennan, M.J., and Schwartz, E., (1985), "Evaluating natural resource investments", Journal of Business, Vol. 58 (2), Pp. 135 – 157

Cabedo, J, D., and Moya, I., (2003), "Estimating oil price value at risk using historical simulation approach", Energy Economics, Vol. 25, Pp. 239 – 253

Clements, M. P., and Smith, J. P., (1997), "The performance of alternative forecasting methods for SETAR models", International Journal of Forecasting Vol. 13, Pp. 463 – 475

Clements, M. P., and Smith, J. P., (1999), "A Monte Carlo study of the forecasting performance of empirical SETAR models", Journal of Applied Econometrics, Vol. 14, Pp. 123 – 141

Cunningham, N., (2015), "Top five factors affecting oil prices in 2015", OilPrice.Com available at http://oilprice.com/Energy/Energy-General/Top-Five-Factors-Affecting-Oil-Prices-In-2015.html. Accessed on 27th of July 2017.

Dunis, C. L., Laws, J., and Naim, P., (2003), "Applied quantitative methods for trading and investments", John Wiley & Sons, Ltd

Energy Information Administration (2017), "What drives crude oil prices?" July 11, 2017. Washington, DC. Available at https://www.eia.gov/finance/markets/crudeoil/reports_presentations/crude.pdf accessed on 27th July 2017

Fattouh, B., and Lavan M., (2013), "OPEC: what difference has it made?", Annual Review of Resource Economics, Vol. 5, Pp. 427 – 443

Fattouh, B., Rahmatallah, P., and Anupama, S., (2015), "The dynamics of the revenue maximization - market share trade-off: Saudi Arabia's oil policy in the 2014-2015 price fall". Oxford Institute for Energy Studies Working Paper, WPM 61.

Frühwirth-Schnatter, S., (2006), "Finite mixture and Markov switching models", Springer Science and Business Media LLC, New York

Garcia, R., and Schaller, H., (2002), "Are the effects of monetary policy asymmetric?", Economic Inquiry, Vol. 40, Pp. 102 – 119

Gouri´eroux, C., and Monfort, A., (1995), "Time Series and dynamic models, translated", Gallo, G., (eds) Cambridge University Press, Cambridge.

Hamilton, J. D., (1989), "A new approach to the economic analysis of nonstationary time series and the business cycle", Econometrica, Vol. 57, Pp. 357 — 384

Huppmann, D., and Holz, F., (2012), "Crude oil market power: a shift in recent years?", The Energy Journal, Vol. 33, Issue 4, Pp. 1 – 2

Huppmann, D., and Holz, F., (2015), "What about the OPEC Cartel?", DIW Roundup: Politik im Fokus, 58.

Hyndman, R., J., and Koehler, A., B., (2006) “Another look at measures of forecast accuracy”, International Journal of Forecasting, Vol. 22, Pp. 679 – 688
Kaastra, I., and Boyd, M., (1996), “Designing a Neural Network for forecasting financial and economic Time Series”, Neurocomputing, Vol. 10, Pp. 215 – 236
Kilian, L., and Murphy, D.P., (2014), “The role of inventories and speculative trading in the global market for crude oil”, Journal of Applied Econometrics, Vol. 29, Pp. 454 – 478
Kilian, L., and Vigfusson, R. J., (2013), “Do oil prices help forecast U.S. real GDP? the role of nonlinearities and asymmetries”, Journal of Business & Economic Statistics, Vol. 31, Issue 1, Pp. 78 – 93
Kim, C. J., Morley, J., and Piger, J., (2005), “Nonlinearity and the permanent effects of recessions”, Journal of Applied Econometrics, Vol. 20, Pp. 291 – 309
Lo, M., and Piger, J., (2005), “Is the response of output to monetary policy asymmetric? evidence from a regime-switching coefficients model”, Journal of Money, Credit and Banking, Vol. 37, Pp. 865 – 887
Meese, R., and Rogoff, K., (1983), “Empirical exchange rate models of the seventies: do they fit out of sample?”, Journal of International Economics, Vol. 14, Pp. 3 – 24
Nigel, M., (2010), “Oil prices – Brownian motion or mean reversion? a study using one year ahead density forecast criterion”, Energy Economics, Vol. 32, Pp. 1485 – 1498
Nwafor, C. N., and Oyedele, A. A., (2017), “Simulation and hedging oil price with geometric Brownian motion and single-step binomial price model”, European Journal of Business and Management Vol. 9, No. 9, Pp. 68 – 81
Panas, E., and Ninni, V., (2000), “Are oil markets chaotic? a non-linear dynamic analysis”, Energy Economics, Vol. 22, Pp. 549 – 568
Perron, P., (1989), “The Great Crash, the oil price shock, and the unit root hypothesis,” Econometrica, Vol. 57, Pp. 1361 – 1401
Perron, P., (2006), “Dealing with structural breaks,” in Palgrave Handbook of Econometrics, Patterson, K., and Mills, T. C., (eds.), Vol. 1, Econometric Theory, Palgrave Macmillan, Pp. 278 – 352
Perron, P., and Vogelsang, T. J., (1992a), “Non-stationarity and level shifts with an application to purchasing power parity”, Journal of Business & Economic Statistics, Vol. 10, Pp. 301 – 320
Pindyck, R. S., and Rubinfeld, D. L., (1998), Econometric Models and Economic Forecasts, 4th edition,
McGraw-Hill, New York.
Ravn, M., and Sola, M., (2004), “Asymmetric effects of monetary policy in the United States, Federal Reserve Bank of St. Louis Review, Vol. 86, Pp. 41 – 60
Sadorsky, P., (2006), “Modelling and forecasting petroleum futures volatility”, Energy Economic, Vol. 28, Pp. 467 – 488
Tang, L., and Hammoudeh, S., (2002), “An empirical exploration of the world oil price under the target zone model”, Energy Economics, Vol. 24, Pp. 577 – 596
Theil, H., (1966), Applied Economic Forecasting; North-Holland: Amsterdam.
U.S Energy Information Administration Analysis (2017), “What drives Crude Oil Prices available at https://www.eia.gov/finance/markets/reports_presentations/eia_what_drives_crude_oil accessed on July 27th 2017
Vasicek, O. A., (1977), “An equilibrium characterization of the term structure”, Journal of Financial Economics, Vol. 5, Pp. 177 – 188
Vogelsang, Timothy J. and Pierre Perron (1998). “Additional test for unit root allowing for a break in the trend function at an unknown time,” International Economic Review, Vol. 39, Pp. 1073 – 1100
Vogelsang, Timothy J. (1993). Unpublished computer program.
Zivot, Eric, and Donald W. K. Andrews (1992). “Further evidence on the Great Crash, the oil-price shock, and the unit-root hypothesis”, Journal of Business & Economic Statistics, Vol. 10, Pp. 251 – 270.

Acknowledgement

We acknowledge the existence of a specific crude petroleum; dubbed Bonny Light crude oil. Bonny oil derives its name from the actual location named Bonny County in Nigeria where it was first discovered and mined for commercial application. This type of oil remains one of the most desirable and sought for oils in the whole world. United States and other Western countries import approximately 70% of the total Bonny oil produced in Nigeria into their energy systems. Currently, oil consumers in other crude petroleum producing countries like United Arab Emirates are really interested in sourcing this precious commodity from the West African nation.
Bonny oil remains popular because of its sulfur content properties. Since the history of oil discovery, Bonny oil features as the crude product with the lowest sulfur content in the oil industry. In this regard, low sulfur content makes refinery procedures easy and economical. In technical application of finished petroleum, sulfur tends to poison anti-knock additives in engine fuels. This means that low sulfur results in ineffective poisoning of the anti-knock agents; hence efficient burning of fuels in combustion engines. In addition, easy processing reduces

emission of poisonous affluent to the earth's environment. With respect to environmental concerns, reduced emissions of pollutants contribute towards mitigation of global warming effects. All these positive qualities are the reasons for popularity of this light oil in subject. Presently, Bonny oil remains the most environmentally suitable type of crude oil for obtaining gasoline and heating gas. Based on increasing demand of Bonny oil, Nigerian companies are stepping up efforts to achieve an appropriate supply level. In March 2013, Nigerian Bonny oil inventory reflected that production had increased by approximately 5% compared to the previous month of February. Upon refinery and blending processes, Niger Delta Company, which is the chief producer of Bonny Light crude oil had gasoline inventory of 1.2 million barrels at the end of February. However, increased in production resulted in a increase of inventory to 1.26 million barrels at the end of March. Therefore, future increase in demand of the light oil may saw a subsequent increase in inventories as per the demand forces.